

Visualizing Seismic Risk and Uncertainty

A Review of Related Research

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Government agencies and other authorities often communicate earthquake risks using maps derived from geographic information systems. Yet, little is known about the effects of these maps on risk perceptions. While mental models research and other approaches are available to inform risk communication text design, similar empirically derived guidance is lacking for visual risk communications, such as maps, which are likely to trump text in their impact and appeal. This paper reviews the empirical research that might inform such guidance. Research on graphs, spatial and visual perception, and map design suggests that graphics increase risk avoidance over numerical risk representations, and countable visuals, like dots, can increase the accuracy of perceived risks, but not always. Cartographic design features, such as color, animation, interactivity, and depth cues, are all candidates to represent risk and uncertainty and to influence risk perception. While there are robust known effects of color (e.g., red = danger), with some cultural variability, animation can increase the salience of otherwise obscure features but is not uniformly effective. Depth cues, dimensionality, and the extent to which a representation depicts versus symbolizes a scene will influence the viewer's perspective and perception, depending on the viewer's familiarity with the scene; their effects on risk perception remain unclear. The translation and representation of technical information about risk and uncertainty is critical to risk communication effectiveness. Our review suggests a handful of candidate criteria for evaluating the effects of risk visualizations, short of changes in behavior: accuracy, accessibility, retention, and perceived risk and usefulness.

Key words: visualization; risk communication; uncertainty; seismic; maps

Introduction

Earthquake decision-making processes rely on effective communication of risk and uncertainty. What is effective, however, is likely to vary by the type of decision maker. Business and political decision makers in private companies and local governments may require different depictions of risk than technical audiences, such as engineers and seismologists, some of whom are well versed in probability theory. Building on research in human-computer interaction, risk communication, and spatial analysis and exposure to mapped data,¹⁻³ this review aims to build the foundation for designing and testing alternative ways to communicate risk and uncertainty for low-probability high-consequence events, with a focus on advancing what is known about the effects of spatial information, communication of risk, and uncertainty in spatial information and how

these can be tailored effectively for different earthquake decision makers.

Natural disasters, such as hurricanes and earthquakes, are spatial in nature. For this reason, geographic information science (GISc) tools are often included in software designed for natural hazard prevention and mitigation decisions. Construction of risk in the mind of the perceiver depends, at least in part, on the representation of the underlying hazard,⁴ which suggests that the design of the user interface for natural hazard mitigation software will influence risk perceptions and decision-making processes. There is, however, little empirical research on the effects of cartographic spatial representations and other visualizations on risk perception and decision making. This paper reviews the literature on risk visualization design and human spatial and risk perception to lay the ground for future research at their intersection.

Methodology

A general search of the expanded Social Science Citation index for the terms "risk visualization" produced no results. In contrast, searching for "visual* and risk*" produced over 8000 publications. Selecting only those

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that included the terms communication and perception reduced the findings to 13 studies, of which only seven were relevant.^{5–11} For this reason, we searched multiple databases and the internet using a wide variety of search terms, tools, and citation tracking.

Studies of visual representation of risk to date have focused on statistical graphics^{9,10,12,13} and symbols, such as warning symbols,¹⁴ although recent work on the effects of video footage is a notable exception.^{8,15,16} Rarely has research on cartographic representations of risk included tests of their effects on risk perceptions and decisions. To develop a general framework for such tests, we draw on research by MacEachren and Tversky in addition to risk communication research. We also look at visualization research by Pang and colleagues on visualizing uncertainty in geographic information systems (GIS),¹⁷ and a review of visualization in the social sciences.¹⁸

Structure

The following section reviews pertinent background knowledge on risk, including definitions of risk—how risk assessment, risk perception, risk communication, and risk visualization are related—and the increasing significance of GIS and visualization for natural disasters. The subsequent sections discuss findings from past research on risk visualization and perceived risks and propose a framework for evaluating risk visualizations. In the last section of the paper, we propose future research directions for risk visualization.

Perspectives on Risk and Related Concepts

Risk is generally defined in formal analyses as the perceived magnitude of loss times the probability of loss or harm (i.e., adverse consequence) from an event.¹⁹ Related formal conceptions of risk include, but are not limited to, probability of loss, size of credible loss, expected loss (probability multiplied by the size of loss), and the variance of the probability distribution over all possible consequences.²⁰ Some hazard researchers, such as Cutter²¹ and Collins,⁴ define risk as the probability of hazard and define hazard in terms often used by risk researchers to define risk as a broad concept that “incorporates the probability of the event happening, but also includes the impact or magnitude of the event on society and the environment, as well as the sociopolitical contexts within which these take place.”²² Radke *et al.*²³ define “risk” as “the potential or likelihood of an emergency to occur;” but “hazard” as “generally a

reference to physical characteristics that may cause an emergency.”

In this review, hazard is defined as the underlying physical events or acts that pose potential harm, similar to the definition of Radke *et al.*, whereas risk is treated as a broader construct, incorporating the probability of realizing the potential adverse consequences or harm as well as the magnitude of harm.²⁴ Note that both definitions of risk and the process of defining risk can be controversial.²⁵

Risk Assessment and Risk Perception

Risk assessment is a formal approach to evaluating risk¹⁹ and generally includes four steps^{26,27}: “hazard identification, dose–response assessment, exposure assessment, and risk characterization.” GISc is playing an increasingly important role in assessing the risk of natural hazards.²⁸

In contrast to formal risk assessments conducted by risk experts, risk is also assessed intuitively by lay people, and these assessments are often called “subjective risk assessments” or “risk perceptions.” Expert risk estimates tend to differ from subjective risk assessments in several ways.^{29,30} Research by Fischhoff, Slovic, Lichtenstein, and others applies a psychometric paradigm to characterize risk perceptions.^{31,32} This involves attitude ratings, such as how dreadful or how familiar a person rates a risk. The findings suggest characteristics of risks that lay people are more likely to accept and of risks that they would be more likely to find unacceptable. This, together with other research,³³ demonstrates that risk communication that does not address recipient’s attitudes and decision needs has an increased likelihood of failure.

A distinction is often drawn between objective measures of risk, quantified roughly as $\text{Risk} = \text{probability} \times \text{consequence}$, and perceived measures of risk, which include other characteristics of risk. This distinction is tenuous. From the formal definitions alone, it is evident that there is no hard and fast distinction between objective and perceived risk (i.e., what is counted as credible loss depends on agreed perceptions and expectations in a community). Risk is, in part, an epistemological problem. The concept of risk depends on how people assess probabilities and what they perceive as harmful consequences. Hence, the distinction between objective and perceived risk is somewhat nebulous.

Risk Communication

Risk communication became a distinct factor of risk management in the 1980s, with the purpose of increasing public and risk managers’ knowledge of risk issues on one hand and stakeholder participation in risk

management on the other.²⁶ Risk communication is generally defined as a dialogue among interested parties—risk experts, policy makers, and affected general public.²⁶

Communicating about high-consequence low-probability risks poses a particular challenge.¹⁹ Risk, by definition, must be related to the perceived and expected consequences of some hazard. The challenge lies in the fact that low-probability risks have seldom been experienced by recipients or been closely related to their lives. Some natural disasters, such as earthquakes, are within this high-consequence low-probability category.

The visual representation of risk (i.e., the visual communication of risk), like other representations of risk, is likely to be a variable in the construction of risk judgments. Risk judgments and choices are often constructed in response to questions about them rather than pulled intact from long-term memory.^{34,35} Thus, understanding how representations of risk affect judgments and decision making is vital to our understanding of risk management and decision-making processes.

Technological and environmental risks have an obvious spatial dimension. Floods, mudslides, and avalanches as much as toxic spills, explosions, transportation of dangerous goods, or hazardous waste management are all spatially distributed problems.³⁶ Further, specific evidence from natural disaster research suggests that the construction of risk in the mind of the perceiver is dependent upon the representation of the hazard being addressed^{4,35}; for disaster management, such representations are usually spatial in some form. The representations, perhaps as much or more than the nature of the hazard, affect the perception of risk and the decision-making process concerning the risk. Further, some risks are more “accessible” to the perceiver in that they are salient and loom relatively larger in the perceiver’s mind than other statistically comparable risks.^{37,38}

Risk Visualization

While language is one of the oldest communication tools and is central in risk communication, visual displays can be more effective than language in some contexts^{4,39,40} and can strongly influence risk perceptions.¹⁵ Risk communication is also a process to bridge differences between various risk perspectives. The evidence reviewed below suggests that visual representations affect the way both experts and nonexperts construct or perceive risk. Visual representations of risk may dominate others, given that vision is the dominant sense.⁴¹ For this reason, visual representations

may also elicit stronger affective responses than other representations.

Cartographic visualization serves a variety of map-use goals.⁴² Although all map use transfers information and promotes visual thinking, map use can vary greatly in terms of which function is emphasized. Taking into account different audiences, data, and interaction levels, map-use goals fall into four categories: exploration, analysis, synthesis, and presentation.⁴² Visualization for presentation concerns situations where the information is known to the presenter but not to the recipients. However, public presentation is not confined to predetermined message transfer. It can also prompt new insights on the recipient’s part through interactive tools. Indeed, interactivity has become increasingly important in strategies to achieve all four goals. Whether interactivity is emphasized or not, MacEachren and Kraak suggest that the *transfer of spatial knowledge* rather than *creation of new knowledge* should always be the top priority in presentation strategy.⁴²

Although not built exclusively for data representation, GIS include an array of features to facilitate the representation of spatial data. These features can be described as the “geovisualization” function of GIS.⁴³ They include summary charts and freestanding tables; two-dimensional and three-dimensional animation designed to support visual exploration of spatio-temporal data sets; three-dimensional computer modeling; interactivity through linking and brushing of multiple views of the data; and flexible combination of available layers for representation.⁴³ A study by Collins⁴ shows greater perceived vulnerability and intentions to act after use of a GIS tool to represent risk from a natural hazard compared to reading a brochure about the same risk.

Perspectives on Visualization of Risk and Uncertainty

Pang and colleagues review existing uncertainty visualization techniques and their corresponding application situations⁴⁴ and present new uncertainty visualization techniques for scalar, multivariate, vector, and tensor data in a variety of applications. This approach provides a toolbox of uncertainty visualization techniques, most of which remain to be tested for their effects on users. Pang proposes two approaches to classifying uncertainty visualization methods.⁴⁵ The first is how uncertainty itself is represented, the second is according to how uncertainty is encoded into the visualization—that is, whether it is singled out and mapped as a separate layer or treated as an integral part of the data set and mapped in a holistic fashion.

One could view Pang's two approaches as corresponding to the extrinsic and intrinsic approaches described by MacEachren and colleagues.^{42,46,47} Howard and MacEachren divide the existing cohort of visualization techniques into intrinsic and extrinsic approaches.⁴⁸ The intrinsic approach they define as changing the appearance of an object. The extrinsic approach they define as the use of "additional symbols to provide information about an object." MacEachren *et al.*⁴⁷ propose that the intrinsic approach is more apt at communicating overall uncertainty, while the extrinsic approach is more suitable for conveying specific locational uncertainty.

Empirical studies to date do not arrive at definite conclusions regarding whether including uncertainty visualization is likely to be more helpful for decision making than excluding it or even whether including uncertainty visualization could, on the contrary, be disruptive to the decision-making process in some cases.^{46,49} There is also no definitive evidence whether, in cases where including uncertainty visualization is helpful, that helpfulness varies by types of decision makers, since decision-making processes and information needs may differ substantially between experts who are versed in probability concepts and novices who are not. When uncertainty visualization is incorporated, the existing literature is inconsistent on what the best uncertainty visualization methods are; even though many methods have been suggested, only a few have been empirically evaluated. Identifying this as a future research challenge, MacEachren and colleagues⁴⁷ call for diverting the focus from uncertainty visualization techniques per se to the relationship between uncertain visualization and decision-making outcomes in order to develop "methods and tools for interacting with uncertainty depictions" and for evaluating the usability and utility of uncertainty visualization renderings.

In sum, MacEachren and colleagues⁴⁷ demonstrate the need for empirical tests of the effects of cartographic visualization and provide a research design framework for doing so. Pang *et al.*⁴⁴ offer a complementary view and a rich palette of approaches to representing uncertainty. MacEachren also emphasizes the function of visualization in facilitating new insights.⁴⁶ Although how a hazard is represented is likely to affect risk perceptions and decisions, not much empirical research has tested this directly. We summarize findings from prior risk and uncertainty visualization research in the following sections in order to develop a guide for future research.

Effects of Risk and Uncertainty Visualizations

Research on visualizations of risk and uncertainty has primarily focused on simple statistical graphics, such as risk "ladders," confidence intervals, pie charts, and the like. Such graphics are effective risk communication aids.^{12,13} Notably, graphical displays of comparative risk increase risk avoidance relative to presenting numbers alone. The following paragraphs summarize the effects of common graphical and symbolic risk visualizations.

Risk Ladder and Related Formats

The risk ladder has been used most extensively to describe environmental hazards (e.g., radon or asbestos).⁵¹⁻⁵⁶ Typically, the risk ladder displays a range of risk magnitudes such that increasing risk is portrayed higher up on the ladder. In sum, the risk ladder effectively helps people "anchor" a risk to upper- and lower-bound reference points. Perceived risk is influenced by the location of risk as much or more than by the actual numbers.⁵³ The efficiency of the risk ladder (e.g., to promote behavior change, understand one's risk) can be enhanced by the addition of an action standard and advice relevant to different risk levels.⁵³ Action standards and advice may influence significantly whether any actions to avert the risk are taken.⁵⁶ However, questions about their use remain.

Stick and Facial Figures

Stick and facial figures have been used most extensively to aid relative risk judgments. In in-depth analysis of visual displays of risk, Stone and colleagues examined how well stick and other visuals (bar graph or asterisks) communicated low-probability events (e.g., tire blowouts and serious gum disease).⁵⁰ The results suggest that graphical displays of comparative risk increase risk aversion relative to presenting numbers alone. However, visual displays did not produce greater risk aversion for higher probability events.⁵³ In tests of whether vivid facial displays can promote skin protective behaviors through fear appeals related to skin cancer, facial displays (like stick figures) affect perceived risk, leading people to be risk averse but no more so than other countable visuals that itemize victims, such as asterisks.⁵⁷

Statistical Graphs

The effectiveness of statistical graphs in communicating risks has been demonstrated in several studies. For example, willingness-to-pay for risk abatement is higher for participants given risk information in

histograms than for those given risk information in numerical form.⁵⁰ Graphic representations of risks more effectively increase participants' risk avoidance than do numbers by weakening cognitive awareness of the upper bounds on the probability of adverse outcomes and by increasing the affective response to them.⁵⁸

Some authors hold that the concept of uncertainty still eludes the general public.⁴⁹ Simple presentation of uncertainty may help; graphic representations can help people understand uncertainty.^{59,60} However, presenting accurate quantitative information alone is not sufficient for a statistical graph to stand out as a good method for conveying information.⁶¹

No single graphical format will perform optimally in all situations. Rather, the effectiveness of a display will be affected by several factors, such as the display characteristics (e.g., use of colors, width of lines, or type and space of legends); conditions of presentation (e.g., lighting or time pressure); data complexity (e.g., number of data points or configuration of the display); the task (i.e., purpose); use characteristics (e.g., cognitive styles); and the criterion for choosing the display (e.g., speed of performance or accuracy).⁶²

Viewers' graph comprehension involves three intermingled processes: (1) viewing the graph and identifying salient features of the graph, (2) recognizing the quantitative information intended to be conveyed by these graphic features, and (3) associating the quantitative information from the graph with the variables presented on the graph.⁶³ Risk communicators will need to take all three into account to use statistical graphs effectively.

Line Graphs

Line graphs are effective for communicating trends in data.^{64–66} In a study of the second phase of graph comprehension, viewers' grasp of the information differed substantially depending on graphic interpretation cues.⁶¹ For example, line-linked-dot graphs convey trend information better than sticks and histograms because line-linked-dot graphs contain interpretation cues that help viewers construct the idea of a trend in their mind.⁶¹

Dots and Related Formats

A few experimental studies have tested the efficacy of using a field of dots to communicating different probabilities of disease.^{53,67–69} These studies test how effective dot or marble visualizations are at conveying low-probability health risks. The results from these studies are mixed. Using dots to visualize the low probability of adverse effects from vaccination could increase participants' willingness to be vaccinated.⁶⁷ However, dot

visualization methods do not necessarily improve the accuracy of viewers' risk perceptions.⁶⁸ For example, the use of marbles to visualize differences in breast cancer risks between women with or without the BRCA1 mutation may improve the accuracy of some women's risk perceptions of breast cancer but may also hinder others.⁶⁹

Pie Charts

Pie charts can be effective for conveying proportion.^{70–73}

Histograms

Histograms are widely used to communicate risk. Although the research linking histograms with perceptions of risk is sparse, it appears that people readily understand and find histograms helpful, and they may induce risk aversion compared with numbers alone.⁵⁰

Effects of Commonly Used Visualization Attributes

As new technologies continue to develop at increasing rates, new visualization techniques emerge continuously.⁴⁴ Researchers are striving to visualize data of increasing dimensionality.⁷⁴ Despite the proliferation of visualization techniques, such techniques are still limited compared to expressed needs.⁷⁵ Commonly used visualization attributes include use of color, interactivity, animation, texture, dimensionality (two dimensional versus three dimensional), and virtual reality. Perceptual and cognitive effects of these are described in the following sections.

Color

Widely used in risk communication, color is an important visual attention guide⁷⁴ and influences risk perception.^{14,75} Wogalter and colleagues¹⁴ find a risk hierarchy for color: red riskier than yellow, yellow riskier than green. Color also influences decision-making processes.⁷⁶ Exposure to red can impair performance by motivating avoidance.⁷⁷ Appropriate use of color can greatly increase the effectiveness of visual communication, while poor use can create confusion.⁷⁸ To use color effectively requires a basic understanding of how people perceive color.⁷⁸ Color categories tend toward universal foci, although there is some cultural variability.⁷⁹

In Ware's⁸⁰ studies of the cognitive effectiveness of color sequences, map information is divided into two categories: metric information, which denotes the quantity (value) of each surface point, and form information, which denotes the shape of the surface. When colors are placed adjacent to one another, the colors tend to interact and thus alter human perception.

For example, when red and blue are put together, blue appears greener and red appears more orange, even though the real colors have not been changed.⁸¹ This is called the simultaneous contrast problem. Color scale along the spectrum works better for presenting value information because it can reduce the simultaneous contrast problem.⁸⁰ Scaling based on lightness or brightness may be helpful in presenting form information, but evidence on this is mixed.⁸⁰

Keller and Keller⁷⁸ argue that human eyes are not sensitive to shape (form information), for which reason contrasting colors can help viewers more easily identify the edge of shapes. Keller and Keller⁷⁸ propose a set of practical guidelines for color use including, for example, how color could enhance three-dimensional effects. They also make the point that when trying to present a phenomenon to an audience, one should choose the color (as well as other techniques) closest to the viewers' experience with that phenomenon, for example, using blue for water or green for forests.

Brewer⁸² tests the use of color on maps with regard to how robust differences between colors are and the degree to which adjacent colors affect perception; she also provides specific guidelines for use of color on maps based on her study results⁸³ as well as other design guidelines.^{84,85} For example, Brewer (page S26)⁸⁵ advises use of light-to-dark color for low-to-high values with a constant hue.

Interactivity

Interactive visualization may amplify the effects of visual data displays.¹⁹ Interactive visualization has the potential to allow users to tailor displays to reflect their individual differences. Even with exactly the same presentation, people's understandings of presentation content vary because of differences in interests, experience, intellectual ability, education, or cultural background. Interactive exploration tools give the audience a chance to freely investigate the part that they are either interested in or about which they still have questions.

Advantages of interactivity stem from: 1) enabling active, instead of passive, participation of the audience; 2) tailoring information for individual users; 3) assisting the risk assessment process; and 4) facilitating visualization of possible risks under different hypothesized conditions (allowing users to ask "what if" questions).⁸⁶ Interactivity may also help if users are overwhelmed by the complexity of a visualization.⁸⁷

However, interactive visualization also poses challenges. Higher dimensionality in visualizations, which have become increasingly popular in practice, may both necessitate and challenge interactivity.⁸⁸ On one

hand, three-dimensional representation complicates visual phenomena, thus making interactive exploration by the viewers more important; on the other hand, three-dimensional environments also require control of more degrees of freedom.⁸⁸ There is also generally a trade-off between accuracy and interactivity under current hardware capacity and technology.⁸⁸ Interactive visualization asks for real-time response, which often employs fast, but less accurate, algorithms. Visualization and algorithmic accuracy trade off against speed. Increasingly larger data sets, coupled with limitations of currently available computer hardware capacity, can slow retrieval of data at "interactive rates."⁸⁸ However, most inaccuracies of fast, although approximate, rendering are largely undetectable, even when put side-by-side with the more accurate rendering.⁷⁸ Fast interpolation techniques are helpful when one simply wants to use animation or interactive exploration to look for anomalies or interesting features in the data. In pursuit of improved interactivity, one approach would be to use techniques from geovisualization, such as dynamic linking and brushing and the highlighting of clusters and outliers, with fast interpolation where necessary.

Animation

Animation simulates continuous phenomena through the display of a discrete collection of images.⁸⁹ As described by MacEachren *et al.*,⁴⁷ animation can represent uncertainty directly (for example, through the use of "long duration in color" to represent "high certainty of classification") and could represent uncertainty indirectly by animating sequences of different potential realizations. MacEachren *et al.*⁴⁷ also consider animation an effective technique for conveying spatial and temporal uncertainties and helping viewers distinguish between them (e.g., in predictions).

Motion, that is, change over time, is critical for feature identification—"objects that are virtually invisible on individual static scenes will pop out of an animated time series display."^{46,90} Motion, like color, is a key driver of human attention and perception.⁷⁴ Risk communication designers should be sensitive to the speed of animation relative to the complexity of the changing information and consider adding appropriate sound effects or narrative comments.⁷⁸ Considerable research on animation in visual representations of scientific and other information has produced mixed findings regarding effectiveness.^{91,92} To be effective, animation should be spatially and temporally contiguous with other information, coherent (without extraneous features or effects), and not redundant.⁹³

Texture

Texture and grain refer generally to the same attribute in spatial representations.⁴⁷ A study by Tamura *et al.*⁹⁴ identifies discrepancies between human perceptions and how textural features are computerized. More recent research identifies four reliably perceptible attributes of texture: coarseness, regularity, lightness, and contrast.⁹⁵ Texture or grain is a strong candidate for representing uncertainty information using static methods⁴⁷ alongside dynamic methods, such as animation and interactivity.

Dimensionality: Two Dimensionality versus Three Dimensionality

Some would consider moving from two-dimensional map rendering to a three-dimensional visual environment the next step in risk visualization. Adding perspective lines to a representation can induce viewers to take an “insider” perspective on a scene.^{96,97} However, although people may adopt differing mental models after viewing graphics with different perspective lines, three dimensionality is not necessarily better than two dimensionality. In fact, two dimensionality and three dimensionality appear equally accurate and effective in some regards.⁹⁶ In tests of their Spatial Framework model, Bryant and Tversky⁹⁶ find that viewers do not need many depth cues to engage an “insider view” if the situation visualized is the one they are *familiar* with. This suggests that when communicating high-consequence low-probability hazards, which have seldom been experienced by the viewers, diagrams with relatively weak depth cues may not be sufficient to induce an inside perspective, but three-dimensional rendering or modeling will be helpful to achieve this goal, if desired (MacEachren⁴⁶ provides a “taxonomy of depth cues” and related applications). People will use intrinsic computation when they can *only* rely on a representation of a scene from a particular vantage point without good depth cues.⁹⁶ It remains to be seen how use of three-dimensional modeling affects risk perceptions.

As noted above, the study by Collins⁴ shows that GIS-based three-dimensional modeling is more effective than a more traditional text-with-graphics brochure for risk communication and improving risk perception. While some studies show that three dimensionality is more effective than two dimensionality for some purposes, such as navigation^{98,99} or responding to integrative questions,¹⁰⁰ other studies find performance decrements with three dimensionality compared to two dimensionality.^{101–103} Viewers’ preference for three dimensionality may exemplify previous findings that user preferences do not al-

ways match user success, as has been found in other contexts.^{47,102}

Smallman *et al.*¹⁰⁴ show that some studies are flawed in claiming that three-dimensional rendering is faster than two-dimensional rendering in conveying information about the third dimension^{105–110} in that they do not control for factors that co-vary with display format, such as the representation of attributes coding the third dimension.

Two dimensionality and three dimensionality each have their distinct advantages. While three dimensionality is better than two dimensionality for facilitating understanding of the shape of simple blocks, two dimensionality is better than three dimensionality for facilitating understanding of the relative position of two objects.¹¹¹

Another issue with three-dimensional rendering is level of detail. In line with previous discussions regarding interactivity, the study by Reddy¹¹² proposes that it is not necessary for computer three-dimensional graphics to provide a lot of details to viewers, which is a common practice in many current visualization projects. His argument is based on the physiology of the human eye, which is incapable of interpreting a lot of detail. Reddy¹¹² suggests deleting imperceptible details from three-dimensional graphics to optimize rendering performance.

Virtual Reality

Virtual reality has been discussed by many as a future direction for risk visualization.^{88,113,114} Virtual reality with real-time interaction promises to allow users to immerse themselves in virtual worlds.¹¹⁵ The level of the sense of immersion should far exceed that evoked by three-dimensional environments.

Evaluating Risk Visualization Design

To date, visualizations have been evaluated for their effects on task performance and, in some cases, for their effects on risk attitudes. Few studies, if any, have addressed both. For risk communicators, the value of visualizations of risk and uncertainty is a function of how they influence perception and cognition to achieve the risk communication goals. A starting point is that risk visualizations should support users’ needs. To that end, Tufte’s¹¹⁶ popular perspective on data usability and accessibility suggests the following framework:

1. Can viewers see the data?
2. What purposes do users have? Is the purpose of the visualization served? Do the visualizations

facilitate seismic risk mitigation decisions? What effect do they have on such decisions?

3. Can viewers focus on the substance rather than methodology, graphic decision, the technology of graphic production, or something else? Does the visualization facilitate comparisons?
4. Can the viewer see the data at several levels of detail? Are the visualizations closely integrated with the statistical and verbal descriptions of a data set?

Based on the above and the research reviewed in this paper, we propose the following measures of visualization effectiveness for cartographic visualizations of risk and uncertainty:

1. accuracy and congruence—Does the viewer perceive statistical information accurately from the visualization? Has the audience perceived the risk information the presenter intended to convey? To measure this requires comparing perceptions with the data used to create the visualization.
2. accessibility—Does the visualization make the information more digestible and accessible? This could be measured in terms of information retrieval time. Some visual properties are more eye-catching than others.^{97,117–120} Discrimination is a related concept. Discrimination can refer to detecting the difference between two perceptual units⁴⁶ or detecting the difference between a perceptual unit and its background.¹¹⁸
3. retention—Does the risk visualization technique increase retention of risk information? How long does the viewer remember it?
4. change in perceived risk—Does the visualization change the viewer's risk perception in the direction intended by the visualization designer?²⁴ This should include measures of both affective and cognitive responses.
5. subjective measures of quality and usefulness, in line with Tufte's recommendations.

Future Research Directions

Abstraction and Perception

This review has focused primarily on visualization research in psychology, education, and geography. Most of that research has focused on statistical graphics to represent risk or uncertainty or on specific visual attributes of spatial and other representations, such as color and animation. Remarkably little literature has examined the effects of cartographic visualizations of

risk and uncertainty on risk attitudes and decisions. It has been demonstrated repeatedly that graphical representations of risk can increase risk aversion to a greater extent than numerical representations of the same risk.^{50,58} This effect appears to stem from both cognitive and affective processing of the representation. Similar effects should, in theory, result from the use of maps to visualize risks.

As Brenner¹²¹ points out, representations fall on a description to depiction continuum, suggestive of an iconic to symbolic continuum that applies more generally to visual representations.³⁹ Depictions can correspond directly to percepts, judging from the similarity of the cognitive processes evoked for each. Thus, depictions are likely to drive perceptions much as the stimuli they depict would. At the other end of this continuum, symbols may also play an important role; use of symbols to denote landmarks on a map, for example, might cue a change of perspective and hence perception. Better understanding this continuum should enable risk communicators to use visualizations more effectively.

Developing a Toolbox of Effective Visualization Techniques

Further research is needed to design and test alternative ways to communicate risk and uncertainty for low-probability high-consequence events. Additional testing would be helpful to enrich our knowledge about perception in relation to visualization techniques, especially of interactivity, two dimensionality–three dimensionality, and animation. Such test results could lead to a “best practice” visualization toolbox for visualization packages and practices. What we learn about perception should provide a stronger basis for defaults in visualization packages in the future.

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Conflicts of Interest

The authors declare no conflicts of interest.

References

1. ANSELIN, L.I. & Y.K. SYABRI. 2006. GeoDa: An introduction to spatial data analysis. *Geographical Analysis* **38**: 5–22.

2. ANSELIN, L., Y.-W. KIM & I. SYABRI. 2004. Web-based analytical tools for the exploration of spatial data. *Journal of Geographical Systems* **6**: 197–218.
3. POTTS, L. 2003. Mapping Environmental Risk of Breast Cancer. *Health Promotion Research Newsletter* **27**: 2–3.
4. COLLINS, R.F. 1998. Risk visualization as a means for altering hazard cognition. Unpublished Dissertation, University of South Carolina, South Carolina.
5. EDWARDS, A.G.K., R. EVANS, J. DUNDON, *et al.* 2006. Personalised risk communication for informed decision making about taking screening tests. *Cochrane Database of Systematic Reviews* (4).
6. EIBNER, F., R. BARTH, A. HELMES & J. BENDEL. 2006. Variations in subjective breast cancer risk estimations when using different measurements for assessing breast cancer risk perception. *Health Risk & Society* **8**: 197–210.
7. MCCOMAS, KA. 2006. Defining moments in risk communication research: 1996–2005. *Journal of Health Communication* **11**: 75–91.
8. ENGELBERG, E. & L. SJOBERG. 2005. Perceived reality of visually mediated hazards and beliefs about risk. *Applied Cognitive Psychology* **19**: 899–912.
9. HOLLOWAY, R.M., C. WILKINSON, T.J. PETERS, *et al.* 2003. Cluster-randomised trial of risk communication to enhance informed uptake of cervical screening. *British Journal of General Practice* **53**: 620–625.
10. LEE, D.H. & M.D. MEHTA. 2003. Evaluation of a visual risk communication tool: effects on knowledge and perception of blood transfusion risk. *Transfusion* **43**: 779–787.
11. DREW, C.H., D.A. GRACE, S.M. SILBERNAGEL, *et al.* 2003. Nuclear waste transportation: case studies of identifying stakeholder risk information needs. *Environmental Health Perspectives* **111**: 263–272.
12. LIPKUS, I.M. & J.G. HOLLAND. 1999. The visual communication of risk. *Journal of the National Cancer Institute Monographs* **25**: 149–163.
13. ANCKER, J.S., Y. SENATHIRAJAH, R. KUKAFKA & J.B. STARREN. 2006 Nov-Dec. Design features of graphs in health risk communication: a systematic review. *J Am. Med. Inform. Assoc.* **13**: 608–18. Epub 2006 Aug 23
14. WOGALTER, M.S., V.C. CONZOLA & T.L. SMITH-JACKSON. 2002. Research-based guidelines for warning design and evaluation. *Applied Ergonomics* **33**: 219–230.
15. LERNER, J.S., R.M. GONZALEZ, D.A. SMALL & B. FISCHHOFF. 2003. Effects of fear and anger on perceived risks of terrorism: a national field experiment. *Psychological Science* **14**: 144–150.
16. LEISEROWITZ, A. 2004. Before and after The Day After Tomorrow: a U.S. study of climate change risk perception. *Environment* **46**: 22–37.
17. LUO, A., D. KAO & A.T. PANG. 2003. Visualizing Spatial Distribution Data Sets. Joint EUROGRAPHICS - IEEE TCVG Symposium on Visualization.
18. ORFORD, S., D. DORLING & R. HARRIS. 1998. Review of Visualization in the Social Sciences: A State of the Art Survey and Report. <http://www.agocg.ac.uk/train/review/review.pdf>
19. BOSTROM, A. & R. LÖFSTEDT. 2003. Communicating Risk: Wireless and Hardwired. *Risk Analysis* **23**: 241–248.
20. VLEK, C. & C. CVETKOVICH (Eds) 1989. *Social Decision Methodology for Technological Projects*. Kluwer Academic Publishers (now Springer). Dordrecht, Netherlands.
21. CUTTER, S.L., Ed. 2001. *American Hazardscapes: The Regionalization of Hazards and Disasters*. Joseph Henry Press, Washington, DC.
22. WHYTE, A.V.T. & I. BURTON, Eds. 1980. *Environmental Risk Assessment*. John Wiley, Chichester, England.
23. RADKE, J., T. COVA, M.F. SHERIDAN, *et al.* 2000. Application Challenges for Geographic Information Science: Implications for Research, Education, and Policy for Emergency Preparedness and Response. *URISA Journal* **12**, 15–30.
24. NATIONAL RESEARCH COUNCIL, COMMITTEE ON RISK PERCEPTION AND COMMUNICATION, COMMISSION ON BEHAVIORAL AND SOCIAL SCIENCES AND EDUCATION, COMMISSION ON PHYSICAL SCIENCES, MATHEMATICS, AND APPLICATIONS. 1989. *Improving Risk Communication*. National Academies Press, Washington DC. See Appendix E.
25. FISCHHOFF, B., S. WATSON & C. HOPE. 1984. Defining risk. *Policy Sciences* **17**: 123–39.
26. BOROUSH, M. 1998. *Understanding risk analysis, a short guide for health, safety, and environmental policy making*. Resources for the Future and the American Chemical Council. Washington, DC. Internet edition accessed March 15, 2007 at <http://www.rff.org/rff/Publications/loader.cfm?url=/commonspot/security/getfile.cfm&PageID=14418>.
27. NATIONAL RESEARCH COUNCIL, COMMITTEE ON THE INSTITUTIONAL MEANS FOR ASSESSMENT OF RISKS TO PUBLIC HEALTH. 1983. *Risk Assessment in the Federal Government: Managing the Process*. National Academies Press. Washington, DC.
28. COPPOCK, J.T. 1995. GIS and natural hazards: an overview from a GIS perspective. *In Geographical Information Systems in Assessing Natural Hazards*. A. Carrara, F. Guzzetti, Eds.: 21–34. Kluwer Academic Publishers. Dordrecht, Boston, London.
29. BOSTROM, A. 1998. Risk Perceptions: Experts versus Laypeople. *Duke Environmental Law and Policy Forum* **VIII**: 101–113.
30. MILETI, D.S. 1993. Communicating public earthquake risk information. *In Prediction and Perception of Natural Hazards*. J. Nemeč, J. M. Nigg & F. Siccardi, Eds. Kluwer Academic Publishers. Dordrecht, Boston, London.
31. SLOVIC, P. 1987. Perceived risk. *Science*. **236**: 280–285.
32. SLOVIC, P., Ed. 2000. *The Perception of Risk*. Earthscan Publications Ltd: UK.
33. MORGAN, M.G., B. FISCHHOFF, A. BOSTROM & C.J. ATMAN. 2002. *Risk Communication: A Mental Models Approach*. Cambridge University Press. Cambridge, UK.
34. SLOVIC, P. 1995. The construction of preference. *American Psychologist*. **50**: 364–371.
35. SLOVIC, P. & S. LICHTENSTEIN, Eds. 2006. *The Construction of Preference*. Cambridge University Press. London.
36. FEDRA, K. 1998. Integrated risk assessment and management overview and state of the art. *Journal of Hazardous Materials* **6**: 5–22.

37. FISCHHOFF, B., A. BOSTROM & M.J. QUADREL. 2002. Risk perception and communication. *In* Oxford Textbook of Public Health. R. Detels, J. McEwen, R. Beaglehole & H. Tanaka, Eds.: 1105–1123. Oxford University Press. London.
38. FISCHHOFF, B., R.M. GONZALEZ, J.S. LERNER & D.A. SMALL. 2005. Evolving Judgments of Terror Risks: Foresight, Hindsight, and Emotion. *Journal of Experimental Psychology: Applied* **11**: 124–139.
39. SHAH, P. & A. MIYAKE, Eds. 2005. *The Cambridge Handbook of Visuospatial Thinking*. Cambridge University Press. Cambridge, UK.
40. WOGALTER, M.S., Ed. 2005. *Handbook of Warnings*. Lawrence Erlbaum Associates. Mahwah, NJ.
41. GAHEGAN, M. 2000. Visualization as a tool for geocomputation. *In* Geocomputation. S. Openshaw, R.J. Abraham, Eds.: 253–274. Taylor and Francis. London.
42. MACEACHREN, A.M. & M. KRAAK. 1997. Exploratory cartographic visualization: advancing the agenda. *Computer & Geosciences* **23**: 335–343.
43. ESRI. 2005. A GIS Includes an Intelligent Map and Other Views. Retrieved June, 2005, from <http://www.esri.com/software/arcgis/concepts/geovisualization.html>
44. PANG, A.T., C.M. WITTENBRINK & S.K. LODHA. 1997. Approaches to uncertainty visualization. *The Visual Computer* **13**: 370–390.
45. PANG, A.T. 2001. Visualizing Uncertainty in Geo-spatial data. Paper prepared for and presented to the Computer Science and Telecommunication Board, National Research Council, September 20, 2001, Washington, DC. Accessed March 15, 2007 at <http://www.spatial.maine.edu/~worboys/SIE565/papers/pang%20viz%20uncert.pdf>
46. MACEACHREN, A.M. 1995. *How Maps Work*. The Guilford Press. New York and London.
47. MACEACHREN, A.M., A. ROBINSON, S. HOPPER, *et al.* 2005. Visualizing geospatial information uncertainty: what we know and what we need to know. *Cartography and Geographic Information Science* **32**: 139–160.
48. HOWARD, D. & A.M. MACEACHREN. 1996. Interface design for geographic visualization: tools for representing reliability. *Cartography and Geographic Information Systems* **23**: 59–77.
49. JOHNSON, B.B. & P. SLOVIC. 1995. Presenting uncertainty in health risk assessment: initial studies of its effects on risk perception and trust. *Risk Analysis* **15**: 485–494.
50. STONE, E.R., J.F. YATES & A.M. PARKER. 1997. Effect of numerical and graphical displays on professed risk-taking behavior. *Journal of Experimental Psychology: Applied* **3**: 243–256.
51. UNITED STATES ENVIRONMENTAL PROTECTION AGENCY. 1992. Indoor air radiation (No. EPA 402K92001). Environmental Protection Agency. Washington DC.
52. COVELLO, V.T. 1991. Risk comparisons and risk communications: issues and problems in comparing health and environmental risks. *In* Communicating Risks to the Public: International Perspectives. R.E. Kasperon & P.J.M. Stallen, Eds.: 79–124. Kluwer Academic Publishers. Dordrecht, the Netherlands.
53. SANDMAN, P.M., N.D. WEINSTEIN & P. MILLER. 1994. High-risk or low - how location on a risk ladder affects perceived risk. *Risk Analysis* **14**: 35–45.
54. SMITH, V.K., W.H. DESVOUGES & A.M. FREEMAN. 1985. Valuing changes in hazardous waste Cooperative agreement No. CR-811075: the benefits of hazardous waste-Management regulations using contingent valuation. The US Environmental Protection Agency. Washington DC.
55. SMITH, V.K., W.H. DESVOUGES, F.R. JOHNSON & A. FISHER. 1990. Can public information affect risk perception? *J. Policy Anal. Manage* **9**: 41–59.
56. SMITH, K.V., W. DESVOUGES & J.W. PAYNE. 1995. Do risk information programs promote mitigation behavior? *Journal of Risk Uncertainty* **10**: 203–221.
57. STEPHENSON, M.T. & K. WITTE. 1998. Fear, threat, and perceptions of efficacy from frightening skin cancer messages. *Public Health Review* **26**: 147–174.
58. CHUA, H.F., J.F. YATES & P. SHAH. 2006. Risk avoidance: graphs versus numbers. *Memory & Cognition* **34**: 399–410.
59. IBREKK, H. & M. GRANGER MORGAN. 1987. Graphical communication of uncertain quantities to nontechnical people. *Risk Analysis* **7**: 519–529.
60. MORGAN, M.G., M. HENRION, M. SMALL, 1990. *Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis*. 332 pp., Cambridge University Press. New York. (Paperback edition 1992. Latest printing (with revised Chapter 10) 1998.)
61. SHAH, P., R.E. MAYER & M. HEGARTY. 1999. Graphs as aids to knowledge construction: signaling techniques for guiding the process of graph comprehension. *Journal of Educational Psychology* **91**: 690–702.
62. GILLAN, D.J., C.D. WICKENS, J.G. HOLLANDS & C.M. CARSWELL. 1998. Guidelines for presenting quantitative data in HFES publications. *Human Factors* **40**: 28–41.
63. SHAH, P. & P.A. CARPENTER. 1995. Conceptual limitations in comprehending line graphs. *Journal of Experimental Psychology: General* **124**: 43–61.
64. HOLLANDS, J.G. & I. SPENCE. 1992. Judgments of change and proportion in graphical perception. *Human Factors* **34**: 313–334.
65. MEYER, J., D. SHINAR & D. LEISER. 1997. Multiple factors that determine performance with tables and graphs. *Human Factors* **39**: 268–286.
66. SCHUTZ, H.G. 1961. An evaluation of formats for graphic trend displays (experiment II). *Human Factors* **3**: 99–101.
67. KAPLAN, R.M., Z.B. HAMMEL & L.E. SCHIMMEL. 1985. Patient information processing and decision to accept treatment. *Journal of Social Behavior and Personality* **1**: 113–120.
68. WEINSTEIN, N.D., P.M. SANDMAN & W.H. HALLMAN. 1994. Testing a visual display to explain small probabilities. *Risk Analysis* **14**: 895–897.
69. BATY, B.J., V.L. VENNE, J. McDONALD, *et al.* 1997. BR-CAI testing: genetic counseling protocol development and counseling issues. *Journal of Genetic Counseling* **6**: 223–244.

70. HOLLANDS, J.G. & I. SPENCE. 1992. Judgments of change and proportion in graphical perception. *Human Factors* **34**: 313–334.
71. HOLLANDS, J.G. & I. SPENCE. 1998. Judging proportion with graphs: the summation model. *Applied Cognitive Psychology* **12**: 173–190.
72. SIMKIN, D. & R. HASTIE. 1987. An information processing analysis of graph perception. *Journal of American Statistics Association* **82**: 454–465.
73. SPENCE, I. & S. LEWANDOWSKY. 1991. Displaying proportions and percentages. *Applied Cognitive Psychology* **5**: 61–77.
74. WOLFE, J.M. & T.S. HOROWITZ. 2004. What attributes guide the deployment of visual attention and how do they do it? *Nature Reviews Neuroscience* **5**: 1–7.
75. SOLDAT, A.S. & R.C. SINCLAIR. 2001. Colors, smiles, and frowns: external affective cues can directly affect responses to persuasive communications in a mood-like manner without affecting mood. *Social Cognition* **19**: 469–490.
76. ROGERS, J.E. & R.E. GROOP. 1981. Regional portrayal with multi-pattern color dot maps. *Cartographica* **18**: 51–64.
77. ELLIOT, A.J. 2007. Color and psychological functioning: the effect of red on performance attainment. *Journal of Experimental Psychology: General* **136**: 154–168.
78. KELLER, P.R. & M.M. KELLER. 1993. *Visual Cues: Practical Data Visualization*. IEEE Press. Piscataway, NJ.
79. REGIER, T., P. KAY & N. KHETARPAL. 2007. Color naming reflects optimal partitions of color space. *Proceedings of the National Academy of Sciences of the United States of America* **104**: 1436–1441.
80. WARE, C. 1988. Color sequences for univariate maps: theory, experiments and principles. *Computer Graphics and Applications, IEEE* **8**: 41–49.
81. See <http://webexhibits.org/colorart/contrast.html>.
82. BREWER, C.A. 1997. Evaluation of a model for predicting simultaneous contrast on color maps. *Professional Geographer* **49**: 280–294.
83. ColorBrewer.org
84. BREWER, C.A., W.H. GEOFFREY & A.H. MARK. 2003. ColorBrewer in print: a catalog of color schemes for maps. *Cartography and Geographic Information Science* **30**: 5–32.
85. BREWER, C.A. 2006. Basic mapping principles for visualizing cancer data using geographic information systems (GIS). *American Journal of Preventive Medicine* **30**(2S): S25–S36.
86. STRECHER, V.J., T. GREENWOOD, C. WANG & D. DUMONT. 1999. Interactive multimedia and risk communication. *Journal of the National Cancer Institute. Monographs* **25**: 134–139.
87. CLIBURN, D.C., J.J. FEDDEMA, J.R. MILLER & T.A. SLOCUM. 2002. Design and evaluation of a decision support system in a water balance application. *Computers & Graphics (UK)* **26**: 931–949.
88. ENCARNACAO, J., J. FOLEY, S. BRYSON, *et al.* 1994. Research issues in perception and user interfaces. *Computer Graphics and Applications, IEEE* **14**: 67–69.
89. BRODLIE, K.W. 1992. Visualization techniques. *In Scientific Visualization—Techniques and Application*. K.W. Brodlie, *et al.* Eds.: 37–86. Springer Verlag. Berlin and Heidelberg.
90. FRIEDHOFF, R.M. & W. BENZON. 1989. *Visualization: The Second Computer Revolution*. Harry Abrams. New York.
91. BYRNE, M.D., R. CATRAMBONE & J.T. STASKO. December 1999. Evaluating animations as student aids in learning computer algorithms. *Computers & Education* **33**: 253–278.
92. TVERSKY, BARBRA, J.B. MORRISON & M. BETRANCOURT. October 2002. Animation: can it facilitate? *International Journal of Human-Computer Studies* **57**: 247–262.
93. MAYER, R.E. & R. MORENO. 2002. Animation as an aid to multimedia learning. *Educational Psychology Review* **14**: 87–99.
94. TAMURA, H., S. MORI & T. YAMAWAKI. 1978. Textural Features Corresponding to Visual Perception. *IEEE Transactions on Systems, Man, and Cybernetics, SMC-8* **6**.
95. CHO, R.Y., V. YANG & P.E. HALLETT. 2000. Reliability and dimensionality of judgments of visually textured materials. *Perception & Psychophysics* **62**: 735–752.
96. BRYANT, D.J. & B. TVERSKY. 1999. Mental representations of perspective and spatial relations from diagrams and models. *Journal of Experimental Psychology: Learning, Memory, and Cognition* **25**: 137–156.
97. FRANKLIN, N. & B. TVERSKY. 1990. Searching imagined environments. *Journal of Experimental Psychology: General* **119**: 63–76.
98. DENNEHY, M.T., D.W. NESBITT & R.A. SUMEY. 1994. Real-time three-dimensional graphics display for anti-air warfare command and control. *Johns Hopkins APL Tech. Digest* **15**: 110–119.
99. HASKELL, I.D. & C.D. WICKENS. 1993. Two- and three-dimensional displays for aviation: a theoretical and empirical comparison. *Int'l J. Aviation Psychology* **3**: 87–109.
100. WICKENS, C.D., D.H. MERWIN & E.L. LIN. 1994. Implications of graphics enhancements for the visualization of scientific-data - dimensional integrality, stereopsis, motion, and mesh. *Human Factors* **36**: 44–61.
101. ST. JOHN, M., M.B. COWEN, H.S. SMALLMAN & H.M. OONK. 2001. The use of 2-D and 3-D displays for shape understanding vs. relative position tasks. *Human Factors* **43**: 79–98.
102. ANDRE, A.D. & C.D. WICKENS. October 1995. When users want what's not best for them. *Ergonomics in Design* **10**: 37–41.
103. KELLER T., P. GERJETS, K. SCHEITER & B. GARSOFFKY. 2006. Information visualizations for knowledge acquisition: the impact of dimensionality and color coding. *Computers in Human Behavior* **22**: 43–65.
104. SMALLMAN, H.S., M. ST. JOHN, H.M. OONK & M.B. COWEN. 2001. Information availability in 2D and 3D displays. *Computer Graphics and Applications, IEEE* **21**: 51–57.
105. BAUMANN, J.D., S.I. BLANKSTEEN & M. DENNEHY. 1997. Recognition of descending aircraft in a perspective naval combat display. *J. Virtual Environments*.

- <http://www.hitl.washington.edu/scivw/JOVE/Articles/mdjbsb.html> (accessed March 7, 2008).
106. ELLIS, S.R., M.W. MCGREEVY & R.J. HITCHCOCK. 1987. Perspective traffic display format and airline pilot traffic avoidance. *Human Factors* **29**: 371–382.
 107. BEMIS, S.V., J.L. LEEDS & E.A. WINER. 1988. Operator performance as a function of type of display: conventional versus perspective. *Human Factors* **30**: 163–169.
 108. ANDRE, A.D. *et al.* 1991. Display formatting techniques for improving situational awareness in the aircraft cockpit. *Int'l J. Aviation Psychology* **1**: 205–218.
 109. BURNETT, M.S. & W. BARFIELD. 1991. Perspective Versus Plan View Air Traffic Control Displays: Survey and Empirical Results. Paper presented at the Hum. Factors Soc. 35th Ann. Meeting, Santa Monica, Calif.
 110. WICKENS, C.D. *et al.* 1996. Electronic maps for terminal area navigation: effects of frame of reference and dimensionality. *Int'l J. Aviation Psychology* **6**: 241–271.
 111. ST. JOHN, M. & M.B. COWEN. 1999. Use of Perspective View Displays for Operational Tasks. SPAWAR System Center Tech. Rep. San Diego, CA. 1795. [<http://www.spawar.navy.mil/sti/publications/pubs/tr/1795/tr1795.pdf>, accessed April 2, 2007]
 112. REDDY, M. 2001. Perceptually optimized 3D graphics. *Computer Graphics and Applications, IEEE* **21**: 68–75.
 113. GEOWORLD. 2001. GIS in 3-D—Visualization Shines in Diverse Applications - (continued) Virtual Reality Eases Complex GIS Analysis. Retrieved Oct.10, 2005, from http://www.geoplace.com/gw/2001/0110/0110dv_1.asp
 114. HUANG, B., B. JIANG & H. LI. 2001. An integration of GIS, virtual reality and the Internet for visualization, analysis and exploration of spatial data. *Int. J. Geographical Information Science* **15**: 439–456.
 115. The Virtual Reality Lab (VRlab). Swiss Federal Institute of Technology (EPFL). http://vrlab.epfl.ch/research/research_index.html
 116. TUFTE, E.R. 1983. *The Visual Display of Quantitative Information*. Graphics Press. Cheshire, Connecticut.
 117. WOLFE, J.M., S.R. FRIEDMAN-HILL, M.I. STEWART & K.M. O'CONNELL. 2000. Postattentive vision. *Journal of Experimental Psychology: Human Perception & Performance* **26**: 693–716.
 118. WOLFE, J.M., TREISMAN, A., & HOROWITZ, T. 2003. What shall we do with the preattentive processing stage: Use it or lose it? Retrieved Nov. 02, 2005, from <http://search.bwh.harvard.edu/links/talks/VSS03-JMW.pdf>
 119. TREISMAN, A. 1985. Preattentive processing in vision. *Computer Vision, Graphics and Image Processing* **31**: 156–177.
 120. HEALEY, C.G. 2005. Perception in Visualization. Retrieved Oct. 30, 2005, from <http://www.csc.ncsu.edu/faculty/healey/PP/index.html>
 121. BRENNER, A. 1993. *Cartographic Symbolization and Design: ARC/INFO Methods*. Publication of the Office of Information Resources Management of the US EPA, 1993.